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Modified Particle Swarm Optimization for the Optimum Use of Multi-Reservoir Systems: MRP Complex, Chhattisgarh

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ABSTRACT. The effective operation of reservoirs has been a key concern among the water resources management authorities as a consequence of global water shortages and decreased surface water runoff owing to increasing water demand and the effect of climate change. Water shortages, economic constraints, and environmental concerns have all contributed to the optimization of operations becoming increasingly replaced by new technologies. Optimization operation of water resources system is a challenging issue because of its nonlinearity, multiple constraints, and several dimensions. To address the challenges associated with the operation of the multipurpose Mahanadi reservoir in Chhattisgarh, India. The present study utilizes the application of modified particle swarm optimization (MPSO). The present study was conducted to evaluate the performance of the particle swarm optimization (PSO) model in comparison to the current operating reservoir system, to minimize the sum of squared deviations in downstream release and demand. The average percentage changes in reliability (100.31%), resilience (85.02%), sustainability (24.54%), as well as vulnerability reduced up to 69.54%. The model also had the lowest error parameters in the system such as (RMSE = 1.3892, MAPE = 0.1003, NMSE = 0.1025, MAE = 38.6689, and MSE = 1.9299), despite having the highest R^2, i.e., 0.8974. When applied to the Ravishankar Sagar reservoir, MPSO yields optimal, worst, average, and standard deviation (SD) values of 0.45, 0.56, 0.51, and 0.038, respectively. In terms of optimizing the release and storage rates, MPSO performed consistently better than the PSO and other metaheuristics reviewed from the literature during the study. Therefore, MPSO is advantageous in the search for the optimal reservoir operation policy because it is easy to implement, requires less functional evaluations, and quickly tracks global optimum. Hence this study provides significant evidence that MPSO can be used to effectively solve real optimization challenges.

Keywords: optimal operating policy, MRP Complex, particle swarm optimization, performance evaluation

1. Introduction

1.1. Background of the Study

The social behaviour of birds flocking or fish schooling served as inspiration for the evolutionary computation technique known as modified particle swarm optimization (MPSO) (Sengupta et al., 2018). Optimization problems arise often in many disciplines, and this method has found widespread use in sectors as diverse as engineering, economics, and artificial intelligence (AI) (Xu et al., 2021). This method has proven very useful for overcoming obstacles to the efficient utilization of systems with many reservoirs. To effectively manage water resources, multi-reservoir systems require an integrated operation of numerous reservoirs that are connected (Ehteram et al., 2021). The purpose is to determine, for a certain horizon of time, the appropriate release policy for each reservoir, taking into account such factors as water supply needs, flood prevention, and ecological constraints (Zhang et al., 2019). The standard particle swarm optimization (PSO) algorithm is based on a particle-simulation model, (Yang, 2020). Particles locate the best solution by continuously updating their positions to explore the search space (Freitas et al., 2020). A modified PSO algorithm is used to tackle the unique difficulties of optimizing the performance of multi-reservoir systems (Gad, 2022). This adapted strategy takes into account the system's inherent particularities, such as the presence of several objectives, and the consideration of a wide range of limitations, such as the interconnection of reservoirs.

Furthermore, particle swarm heterogeneity can be improved, premature convergence can be avoided, and dynamic system conditions can be handled with the help of the modified PSO algorithm (Liu et al., 2020). These techniques enable the algorithm to reliably test the search space and modify its behaviour in response to shifting operational requirements (Sarker, 2021). Overall, the modified PSO algorithm for optimal usage of multi-reservoir systems incorporate the benefits of classical PSO with problem-specific changes to meet the rigorous demands of this field (Gad, 2022). This method improves water allocation, flood prevention, and hydropower production by balancing competing goals, and incorporating operators and constraints, while utilizing policies for robust optimization in the field of complex water management systems (Zhang et al., 2021).

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1.2. Relevant Literature Study

Currently, optimization techniques play a significant role in modern water resource management (Roushangar et al., 2021). Rao (1984) optimization methods can be broadly classified into two main categories: classical mathematics-based methods and search or numerical methods. The former relies on mathematical principles, while the latter encompasses both direct and indirect search approaches. In classical and indirect search methods, the requirement is for the objective function to be continuous and have a derivative. Indirect search methods involve exploring the variable space point by point using various algorithms, like random jumps, to find the optimal solution (Rao, 1984). In various engineering problems, the objective function may contain multiple local and global optimal points, making it challenging for classical methods to differentiate and efficiently discover the globally optimal solution (Zeinalie et al., 2021). However, Water resources are renewable, but their volume remains constant, while human water demand is steadily increasing (Roushangar et al., 2021). Over the last century, there has been a six-fold increase in global water demand. However, water resources are facing significant pollution from various sources, such as industrial effluents, agricultural wastewater, and both urban and rural wastewater. These pollutants not only contaminate the water but also surpass acceptable consumption standards (Ghanbari et al., 2014). Furthermore, future scientific action in water resources management and planning relies on the crucial aspect of scientific decision-making. In the realm of water resources management, optimization stands out as a highly suitable tool to address challenges effectively (Ahmadianfar and Zamani, 2020; Roushangar et al., 2021).

Guidelines for optimizing reservoir operation management seek to maximize or minimize reservoir benefits without compromising its objectives and constraints (Ai et al., 2022; Verma et al., 2023). The term "reservoir operating policy" is frequently employed to describe this. While it may seem like an obvious challenge to avoid flooding throughout the monsoon season, water conservation measures must be taken (Kaczmarek and Kindler, 1982; Techarungruengsakul et al., 2022). Therefore, to attain the best possible system performance in reservoir operating issues, decisions on releases in addition to storage must be made over time, while taking into significant differences in inflows and demands (Turner et al., 2021). Linear programming, dynamic programming, and meta-heuristic-based optimization algorithms, etc., are currently the most popular optimization methods (Yeh, 1985; Huang and Yuan, 2004; Liu et al., 2011; Zhao et al., 2011; Zhao and Zhao, 2014; Bai et al., 2015). Factors like reservoir physical characteristics, objective function, constraints, uncertainty in inflows, and climate change all play an integral part in determining which optimization technique is best suited for a given study area (Stretch and Adeyemo, 2018). Consequently, there is no universal optimization technique that can be used for all possible reservoir operations (Dobson et al., 2019). Therefore, it is necessary to generate options and evaluate them in terms of risk when formulating policies for the management and operation of water resources. Typically, these three factors are used to assess risk: (1) The likelihood that certain adverse events will take place. (2) Many unfavorable events over a certain time. (3) The expected number of such events over the same time (Lai et al., 2022). Determining the most efficient practices for operating water storage structures is difficult. Evolutionary algorithms (EAs) have been adopted since conventional approaches have proven ineffective. EAs are a useful tool for determining the best ways to manage water storage facilities (Sharifi et al., 2021). One of the most popular EAs in this area is the MPSO algorithm. Numerous research has used conventional PSO or provided a variant of it (Al-Aqeeli and Mahmood Agha, 2020).

Due to increased demand and limited supply, water scarcity has emerged as a major problem in the modern world (Al-Jawad and Kalin, 2019). Reservoirs serve as a crucial structure for communities dependent on water supply. Reservoir optimization is a conventional concern in water resources management, but its significance has not diminished (Tayfur, 2017; Wan et al., 2018; Chang et al., 2019). The sustainable development plan for water resources heavily relies on reservoirs being operated at their optimum efficiency, as this reduces the likelihood of natural disasters like drought and flooding in the region (Nagesh Kumar and Janga Reddy, 2007; Chang and Chang, 2009; Yang et al., 2016a). For example, a reservoir system can be used for ecological water supply, flood prevention, electricity generation, and more. The optimal operation of a reservoir should take into account multi-objective problems to maximize the total benefits (Sun et al., 2018). Increasing pressures on the world's freshwater supply is a result of human civilization's rapid industrialization. However, striking the right balance between competing economic motives to maximize the overall advantages can be challenging (Yang et al., 2016b).

To reduce the sum of the squared deviation between the supply and the intended demand, a reservoir's optimal water allocation model is typically constructed (Tan et al., 2019). The dynamic programming techniques (Nandalal and Bogardi, 2007) suffer from the curse of dimensionality, while non-linear programming (Arunkumar and Jothiprakash, 2012) approaches have the disadvantage of a slow convergence rate (Yeh, 1985). Furthermore, conventional approaches to nonlinear programming have limitations, including a high computational load, a low convergence rate, and a tendency for achieving merely a local optimum (Huang and Yuan, 2004; Bai et al., 2015).

The genetic algorithm (GA) (Jothiprakash et al., 2011), PSO (Nabinejad et al., 2017), and the simulated annealing (SA) (Kangrang et al., 2011) are all examples of meta-heuristic algorithms have experienced widespread application due to their durability and worldwide searching capabilities, and their efficiency and precision continue to evolve and enhance their performance. Kennedy and Eberhart (1995) proposed the particle swarm algorithm, a form of swarm intelligence algorithm, to model social behaviour. Particle swarm algorithms have been used in many different fields since, unlike GAs, they don't require a complex operator (Monem and Kashkooli, 2017; Wan et al., 2017). Numerous research has been focused on rendering the particle swarm algorithm more efficient and accelerating its convergence. For instance, several parameter-tuning approaches have been proposed to boost algorithm reliability and speed up convergence (Sousa-Ferreira and Sousa, 2017). PSO incorporates certain notable elements of various techniques to promote particle diversity (Qu and Lou, 2013). However, there has only been some number of studies carried out regarding how well the algorithm can accommodate different reservoir operation rules. It may be violated by the output of such an algorithm, leading to undesirable outcomes such as inappropriate losses (Celeste and Billib, 2010), because of the use of random sampling in reservoir optimization models.

In the present study, an MHA such as MPSO was formulated for optimizing reservoir operations, taking into account a time series of varying water demands from agriculture, domestic, and industries, as well as incoming water levels. The Ravishankar Sagar Reservoir is the lowest point where these reservoirs can be drained. The Ravishankar Sagar Reservoir serves a variety of purposes, including hydropower generation, industrial water supply, and municipal water supply. The primary objective of this study is to operate this multi-reservoir system so that the total squared variation among downstream supply and demand is minimized. However, the MATLAB 2017a environment was used to write all of the computation codes.

2. Methods

2.1. Particle Swarm Optimization (PSO)

It is commonly utilized as a metaheuristic technique for water resource planning and management. PSO's key benefit is that it provides nearly optimal solutions with minimal computational effort. It has a strong rate of convergence and is not usually stuck in a local maximum (Chen et al., 2008; Montalvo et al., 2008). Studies show that the PSO model is more efficient than other collective models like genetic algorithms (Nagesh Kumar and Janga Reddy, 2007; Montalvo et al., 2008). Furthermore, the PSO model has two input parameters than GA, showing its convenience and efficiency in reaching a satisfying solution. PSO technique is used to forecast real-time runoffs (Chau, 2004). A novel strategic mechanism called "elitist-mutation particle swarm optimization" was developed (Nagesh Kumar and Janga Reddy, 2007). The EM-PSO findings were compared to standard PSO and GA models, and it was found that EM-PSO performed better than the other two techniques. PSO was compared to the ant colony and GA algorithm; compared to ACO and GA approaches, the PSO method provided plausible and superior water supply challenges (Montalvo et al., 2008; Kong et al., 2017). An algorithm is inspired by animal social behaviour such as insect swarming, schooling, and flocking (Kennedy and Eberhart, 1995). Model cost is low due to its basic theoretical background, coding, and performance. Additionally, it has been employed in various research areas, including unbounded continuous optimization problems and genetic algorithms (Kennedy and Allen, 2001). As a result, particle swarm optimization merely restricts particle velocity and finds the optimum solution for all particles and individual particles, i.e., g-best and p-best. However, each particle has a dynamically controlled velocity based on itself and other particles' flying behaviours (He and Wang, 2007).

The inertia weight is a crucial parameter in the PSO algorithm that affects how particles navigate the search space. During optimization, it regulates how much time is spent exploring and how much time is spent exploiting. Additionally, the previous velocity influences the current velocity in proportion to the inertia weight. Moreover, particles are encouraged to continue moving at their prior speeds due to an increase in inertia weight, which gives them more freedom of movement inside the search region. However, when the inertia weight is decreased, the impact of prior velocities is minimized, which is good for

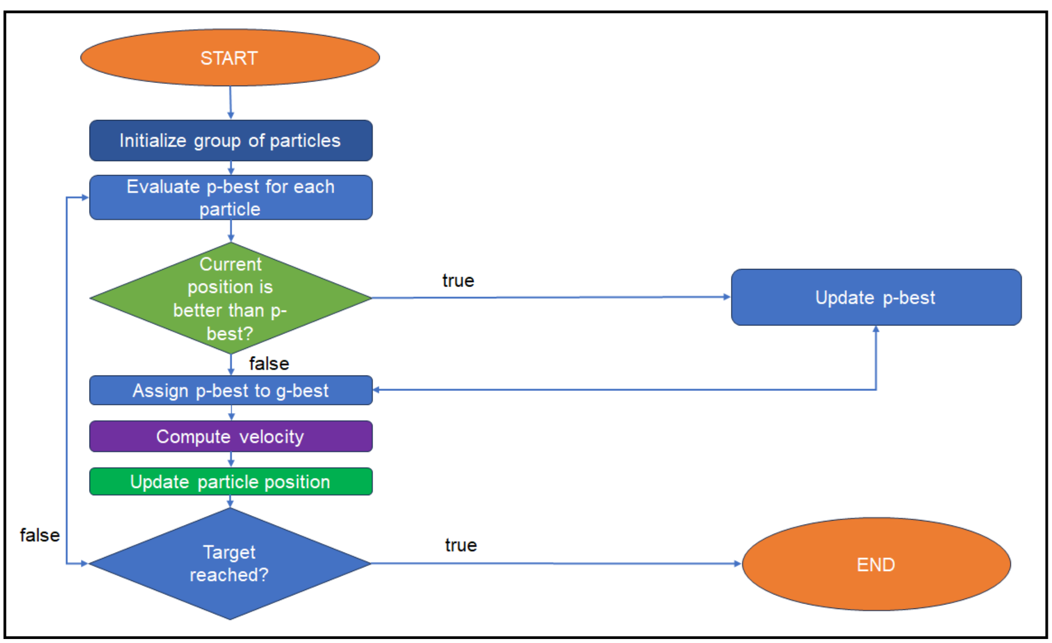

Figure 1. Procedure for accomplishing the PSO.

exploitation because it allows particles to converge toward favourable locations. The PSO algorithm can effectively optimize both exploration and extraction by altering the inertia weight between iterations. At first, a greater inertia weight encourages exploration, leading to a more comprehensive search. As the optimization process continues, the inertia weight is decreased, allowing particles to zero in on the areas immediately surrounding optimal solutions.

The selection of an adequate inertia weight is critical in PSO, as it influences the algorithm's efficiency. Finding the ideal value or adaptively updating the inertia weight in-process requires careful tuning and often requires empirical studies.

When inertia weight w is applied to Equation (1), it controls the impact of the past velocity history on subsequent velocity history. As a result, the inertia weight w, inhibits the population's mutual interaction between global and personal search ability (Abraham et al., 2006). Empirical findings revealed that it is necessary to avoid the design space's global search power increasing and progressively decreasing; the inertial factor should be applied to a large number (Shi and Eberhart, 1998, 1999). The weighting component performance of the PSO model has improved, as Shi and Eberhart (1998, 1999). In addition, it has been shown that the most common method of optimizing a system consists of phases (refer to Figure 1):

$$w = w_{max} \cdot \frac{(w_{max} - w_{min}) \cdot n}{iTer_{max}} \tag{1}$$

where w_{max} is initial weight, w_{min} is final weight. Moreover, n is the number of maximum iterations.

2.2. Modified Particle Swarm Optimization (MPSO)

MPSO stands for modified particle swarm optimization and is an improved form of the more common PSO technique. The convergence rate and search efficiency of the underlying algorithm both are significantly enhanced by the addition of new features found in MPSO (refer to Figure 2).

The purpose of modified PSO is to improve the efficiency and convergence rate of the conventional PSO algorithm utilizing several modifications. Adaptive inertia weight, velocity clamping, as well as regional topology are a few examples of these algorithms. The algorithm may strike a good balance between exploration and exploitation with the help of adaptive inertia weight, which modifies the particle's velocity in realtime. To keep the particles from scattering too far, we can "clamp" their velocities to a narrow range. Particle interactions and information dissemination are characterized by the neighborhood topology in which they occur. As a result of these changes, Modified PSO can effectively probe the search space and identify the best possible solution. Its usefulness has been demonstrated in fields as diverse as engineering, finance, and data mining. Modified PSO is widely used because of its flexibility and efficiency in resolving difficult optimization problems. However, the modified PSO can be classified into two methods which are as follows:

(1) Direct method: In the MPSO algorithm, the direct method was developed. In this method, particles are free to move in any direction toward the best possible global position, rather than being limited to a predetermined search space. By making this adjustment, convergence is accelerated and optimization outcomes are enhanced without particles having to ex-

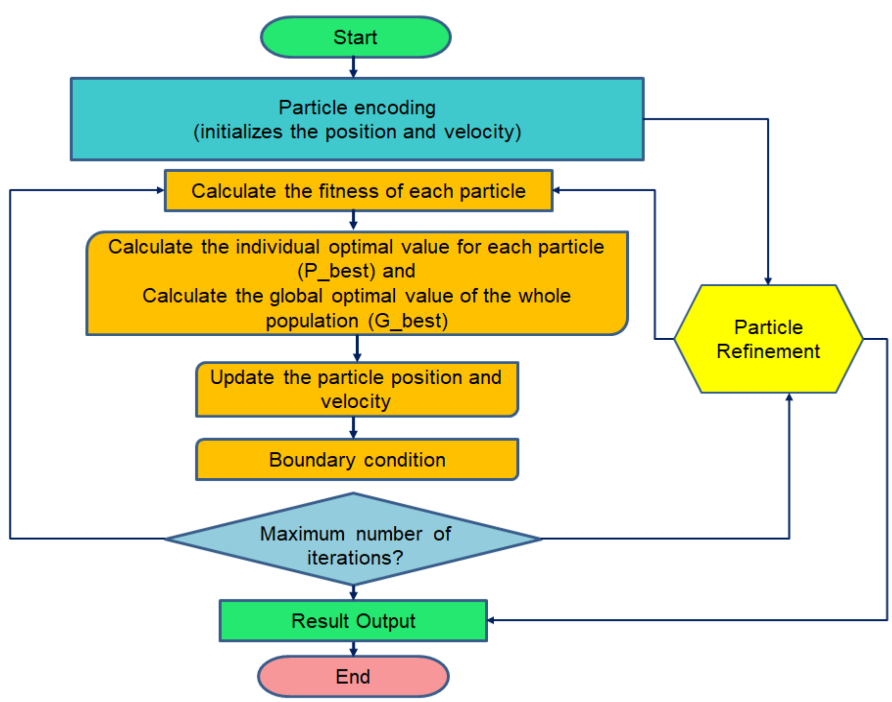

Figure 2. Methodology adapted for MPSO algorithm.

plore the full search space. The direct method uses two different types of information to calculate a particle's speed: the cognitive component, which accounts for the particle's best position to date, and the social component, which accounts for the best position obtained by any particle in the swarm globally. In addition, a direct factor is introduced to show the way to the highest position worldwide. Particles can accelerate their progress toward the optimal solution by combining these variables. Particle velocities in the direct method are based on a combination of the cognitive component, which corresponds to the particle's most recent best position as well as the social component. An additional direct factor is included, denoting progress toward the optimal global location. Particles can accelerate their progress toward the optimal solution by combining these variables.

(2) Indirect method: MPSO is an iteration of the original PSO algorithm that uses an indirect method to tackle the shortcomings of the original. Particles' positions and velocities are not immediately updated in MPSO; rather, a more roundabout method is used. In the indirect method, a set of parameter vectors stands in for individual swarm particles. Particle behaviour is defined by these vectors, which are iteratively updated using equations. Particle movement closer to the optimal solution is affected by the parameters, which govern the particles' velocities and positions. Multiple techniques are incorporated into MPSO's indirect method to better enhance exploration and exploitation. Some examples are using local and global knowledge to direct the search and dynamically altering the parameters. By efficiently employing a set of parameter vectors to steer the search process and increase the algorithm's efficiency, the indirect method in MPSO provides a promising approach to solving optimization challenges.

In practice, it is impossible to take either the direct or indirect approach to the reservoir operation rule. Therefore, there is a potential for wasteful water loss. In this study, we use the period-specific water supply X_t as the iteration variable, and we integrate the operation rule to find V_t and PS_t, which we then use to modify particle trajectories [Equations (2) and (3)]:

$$V_t = V_{t-1} + LS_t - X_t,\ t = 1,\ 2,\ 3,\ \ldots,\ T \tag{2}$$

Thus, the water storage period (t) can be rewritten according to Equation (3):

$$V_t = V_{t,\max} \tag{3}$$

The optimization techniques PSO are both motivated by collective intelligence. As a group of particles (possible solutions) navigates a search space, its members learn from one another and adjust their positions accordingly. In contrast, PSO uses a basic approach, the particles update their positions based on the best solution they have individually found so far (personal best) and the best solution discovered by any particle within the entire swarm (global best). While MPSO retains the spirit of swarm-based exploration while introducing adjustments to improve its performance. These include increasing convergence speed, balancing exploration and exploitation, and making the algorithm more robust.

As the name implies, PSO relies heavily on the position vectors of individual particles (Wu et al., 2019). involves deploying a swarm of particles on an exploration throughout a search space to locate the best possible answers. The position vector of a particle defines its unique identity within the search space. In most cases, the position vector will include coordinates that specify the particle's position in the search space. The optimization problem's number of variables is equal to the vector's number of dimensions. In a two-dimensional scenario, for instance, the location vector would simply be the two coordinates (x, y). In addition, during optimization, particles adjust their location vectors according to their present speed and their degree of gravitational attraction to the most promising solutions. This modification is based on equations that strike a balance between exploration and exploitation. Subsequently, Particles navigate the search space and converge on potentially optimal solutions by continuously modifying their location vectors. The position vectors are vital in determining the behaviour and motion of particles, which in turn enables them to search for the optimal solution collectively.

In the PSO algorithm, particle position vectors are used to dynamically represent possible solutions, allowing for rapid exploration and exploitation of the search space in pursuit of optimal solutions (Marini and Walczak, 2015; Houssein et al., 2021; Gad, 2022). Thus, the simplest way to proceed is to make decisions about supply and storage as iteration variables (Rani and Srivastava, 2016; Karami et al., 2019).

2.3. Reservoir Performance Indices

In the present section, time-based reliability, resilience, sustainability, and vulnerability indices are used to evaluate simulated and observed data performance given various modelling assumptions (Hashimoto et al., 1982). For each time step, the total volume of water supplied was measured and divided by the total water demand to obtain the volumetric reliability; resilience evaluates a system's ability to bounce back after a failure, while vulnerability assesses a deficit. Furthermore, as an integrated measure of the system's performance, we employed the sustainability index (Loucks, 1997), in which each water user's performance criterion is geometrically average (Sandoval-Solis et al., 2011). Furthermore, the detailed description of each performance indices is discussed in Verma et al. (2022a, 2022b).

2.4. Model Evaluations Statistical Indices

The accuracy of the deployed algorithm was evaluated using statistical evaluation indices such as coefficient of determination (R^2), root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE), mean squared error (MSE), and normalized MSE (NMSE) [refer to Equations (4) to (9)] (Willmott, 1981):

$$R^2 = [\frac{\sum (Re_{opt(i)} - \overline{Re_{opt}}) \cdot (Re_t - \overline{Re})}{\sqrt{\sum (Re_{opt(i)} - \overline{Re_{opt}})^2 \cdot \sum (Re_t - \overline{Re})^2}}]^2 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum\nolimits_{t=1}^{n}(Re_{opt(i)} - Re_t)^2} \tag{5}$$

$$MAPE = \frac{100}{n}\sum\nolimits_{t=1}^{n}\left|\frac{Re_{opt(i)} - Re_t}{Re_{opt(i)}}\right| \tag{6}$$

$$MAE = \frac{1}{n}\sum\nolimits_{t=1}^{n}\left|Re_{opt(i)} - Re_t\right| \tag{7}$$

$$MSE = \frac{\sum\nolimits_{t=1}^{n}(Re_{opt(i)} - Re_t)^2}{n} \tag{8}$$

$$MMSE = \frac{\sum\nolimits_{t=1}^{n}(Re_{opt(i)} - Re_t)^2}{\sum\nolimits_{t=1}^{n}(Re_{opt(i)} - \overline{Re})^2} \tag{9}$$

There are two types of optimal release in this equation: Re_t for the optimized algorithm, where $\overline{Re}$ is the mean release overtime period t, and $Re_{opt(i)}$ for the optimal release overtime period t, where $\overline{Re_{opt}}$ is the mean release overtime period t.

3. Mahanadi Reservoir Project Complex: Case Study

3.1. Description of the Study Area

The Mahanadi Reservoir Project (MRP) Complex consists of multiple reservoirs that serve different purposes. Both the Mahanadi and the Pairi basins are included. However, an essential source of water for the Mahanadi is the Pairi River. The river begins in the Bhatigarh hills close to Bindranavagarh in Gariaband District and flows southeast to merge with the Mahanadi close to Rajim in the same district of Chhattisgarh, India (Sahu et al., 2022, 2023). The river is 90 km long and there will be four reservoirs built for this project. From the Sondur reservoir in the Pairi basin, water is supplied via a feeder canal to the Dudhawa reservoir in the Mahanadi basin (Figure 3).

The Sillari River is a branch of the Mahanadi in central-eastern India, and the dam on this river is known as the Murrum Silli Dam (also spelled Madam Silli and Mordem Silli). The governor of the British Raj supervised its construction, and the structure was initially named for her. It was the inaugural dam in Asia that employed siphon spillways, and construction lasted from 1914 to 1923. From Raipur to Madamsilli is around 95 km. It is widely recognized as one of Chhattisgarh's finest examples of structure design. It was designed especially for irrigation. Furthermore, the Kanker district of Chhattisgarh, India is situated at Dudhawa Dam. The dam was not completed until 1964, but its work started in 1953. It is located 21 km from Sihawa and 29 km from Kanker, it spans the Mahanadi River, which originates in the small village of Dudhawa. The retaining wall of the structure is 24.53 m in height and 2,906.43 m in length (Sahu et al., 2022, 2023; Verma et al., 2023). The catchment area for the reservoir is 625.27 km^2. The embankment on the dam's right flank identifies it as an earthen structure.

According to Figure 3, the aforementioned reservoirs are serially interconnected to each other. In addition, the Murumsilli and Dudhawa dams serve as feeder dams for a Ravishankar Sagar reservoir which acts as an outlet to facilitate the water supply for different purposes. Irrigation, Industrial, and Municipal of Raipur, Durg, Mahasamund, and Balodabazar districts mainly. However, the Ravishakar Sagar reservoir is connected to two different canal systems, i.e., Mahanadi main canal (MMC) and Mahanadi feeder canal (MFC). Where MMC is used as an industrial water supply for the Bhilai steel plant Bhilai and MFC is served for irrigation and municipal purposes.

Furthermore, during the present study, the monthly release and demand data (i.e., 1989 ~ 2020) including reservoir characteristics is taken from Water Resource Division Dhamtari, Rudri Circle, Rudri, Chhattisgarh.

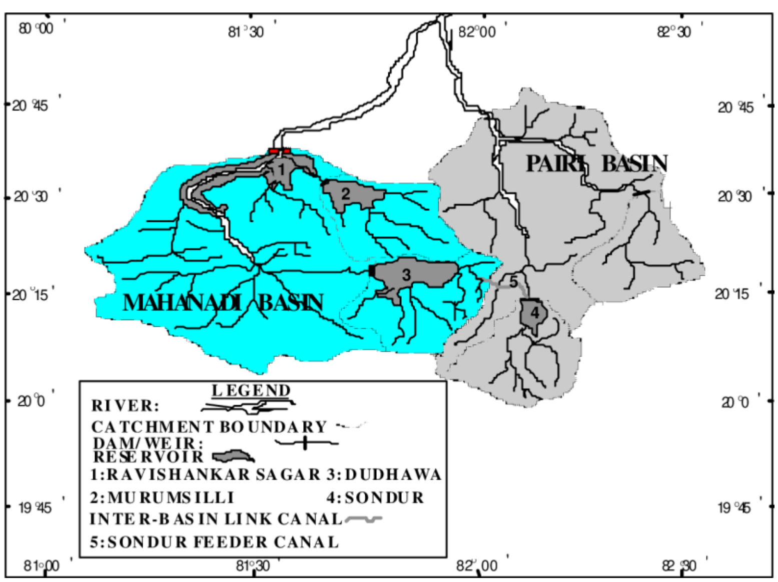

Figure 3. Index map of MRP Complex, Chhattisgarh [source: Jaiswal et al., (2013)].

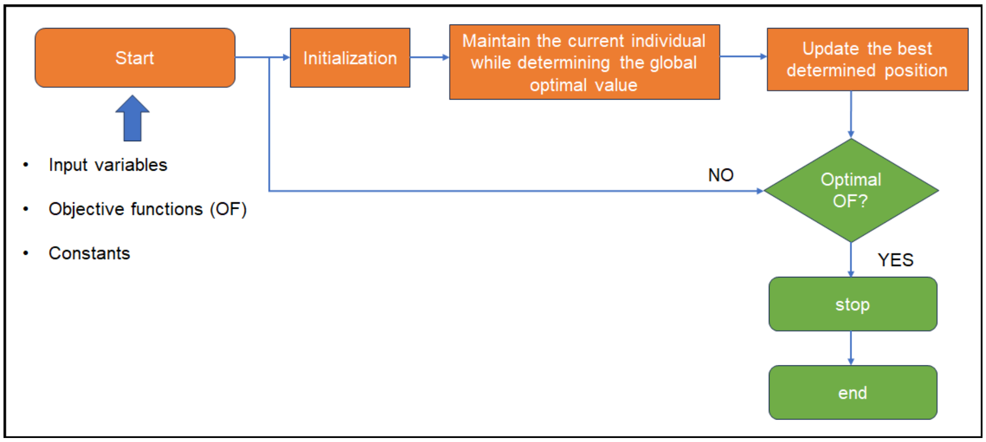

Figure 4. Procedure for model formulation and reservoir optimization [source: Lai et al. (2022)].

3.2. Model Formulation and Reservoir Operation Optimization

This section provides a basic framework for developing and formulating an optimization problem for a reservoir system. Figure 4 shows the most typical steps in the optimization process while utilizing conventional or metaheuristic algorithms.

(1) The choice of decision variables and constraint value, as well as its categorization

(2) Examine the objective function and constraints.

(3) Values for decision variables need to be determined.

(4) When the performance objective has been reached or the criteria for stopping have been met, steps 3 and 4 are carried out. The third step of the operation is typically where the algorithms diverge from one another. Different algorithms use different search mechanisms at the moment. Compared to traditional mathematical optimization methods, the meta-heuristic algorithm has a few advantages (Singh, 2014; Zhang et al., 2019).

3.2.1. Model Formulation

There is a lot of uncertainty around the hydrologic parameters used in reservoir management systems. Uncertainties in mathematical programming models can be handled in either of the following ways: indirectly, through parameter tuning of a deterministic model, or directly, through the use of meta-heuristic-based approaches (like MPSO-driven optimization algorithms).

3.2.2. Penalty Function

The intricacy of the reservoir system being studied will determine the optimum solution. The most frequent conflict in reservoir systems consists of irrigation and hydropower. However, if ecology or navigation serve as additional factors, this will require more constraints, or in certain circumstances, the penalty function (PF) (Sylla, 1995) must be applied in conjunction with the constraints to transform the PF from an infeasible region toward a feasible region, allowing the (Optimization model) MO to be resolved (Long et al., 2023). Therefore, reservoir models must have the flexibility to switch from local as well as global search algorithms as the complexity of the reservoir system increases. This is the only way to ensure top-notch service in terms of release operational policy management.

3.2.3. Objective Function

If a single or multiple objective function was employed in the case study, for example, standard tuning parameters should be adequate. This is because maximizing efficiency and reducing convergence time is an essential concern. However, more complex reservoir models can be used for evaluation. The objective function is given in Equation (10):

$$Z = Minimize \sum_{t=1}^{12} (RI_t - DI_t)^2 \tag{10}$$

where RI_t = Monthly irrigation release, and DI_t = Monthly downstream irrigation demand.

(1) Mass Balance Equation

Final storage equals the monthly inflow during the period t mines monthly water release during the period t mines monthly evaporation loss (all the data are in months):

$$S_{t+1} = S_t + I_t - E_t - R_t - O_t,\ t = 1,\ 2,\ 3,\ \ldots,\ N \tag{11}$$

where S_{t+1} is final storage, S_t is initial storage, I is inflow, R_t is water release, and E_t is evaporation loss.

(2) Release Constraints

The irrigation, industrial, and domestic release in month t should be less than or equal to the irrigation, industrial, and domestic demand in that month, as shown in Equation (12):

$$RI_t \le DI_t,\ t = 1,\ 2,\ 3,\ \ldots,\ 12 \tag{12}$$

(3) Storage Constraints

In any particular month, reservoir storage should not exceed the reservoir's capacity and should not fall below the dead storage capacity, which is indicated in Equation (13):

$$S_{min} \le S_t \le S_{max} \tag{13}$$

where S_{min} = Dead storage (M·m^3); S_{max} = Maximum storage (M·m^3).

(4) Evaporation Loss

Losses due to evaporation in reservoirs over time t, where t is a function of current reservoir storage. For evaporation losses, the ideal expression is as follows:

$$E_t = a_t + b_t \cdot \left[\left(\frac{S_t + S_{t+1}}{2} \right) \right],\ \forall t = 1,\ 2,\ 3,\ \ldots,\ 12 \tag{14}$$

(5) Overflow Constraints

When the reservoir's storage capacity exceeds the reservoir's maximum capacity, the overflow constraint minimizes spills. The relevant limitation can be stated as follows:

$$O_t = S_{t+1} - S_{max},\ \forall t = 1,\ 2,\ 3,\ \ldots,\ 12 \tag{15}$$

$$O_t \geq 0,\ \forall t = 1,\ 2,\ 3,\ \ldots,\ 12 \tag{16}$$

The developed programs are run using the meta-heuristic algorithm models that have been written in MATLAB programming language on an Intel (R) Core (TM) 8GB RAM @ 1.60GHz. They are employed for two different reservoir operation periods. The reservoir system operation model is for a single year, i.e., NT = 12. The reservoir operation in the RSOM-II model is for a relatively long time, about 31 years (NT = 372). In the following part, the outcomes of these two models will be discussed in the results and discussion section.

However, for a better understanding of reservoir behaviours and what is the importance of any input and output in the reservoir system, Figure 5 represents the schematic view of Ravishankar Sagar Reservoir including all the variables for reservoir formulations.

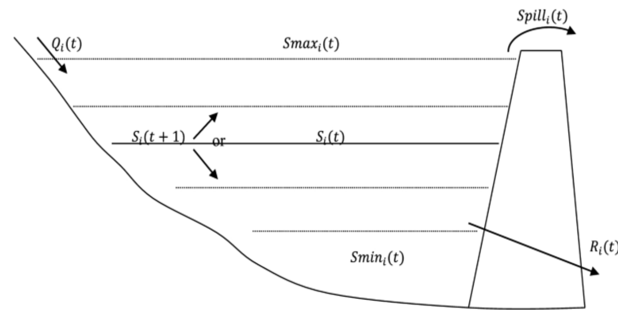

Figure 5. Graphical representation of reservoir system [source: Lai et al. (2022)].

4. Results and Discussion

Studies were conducted employing inertia weight damping ratio (w-damp), the number of search agents, and the number of iterations, with the parameters modified within the following range since MPSO depends on fine-tuning its fundamental parameters. $c_1 = c_2 = 2$ (Kennedy and Spears, 1998), w = 1, w-damp = 0.9 (Reddy and Kumar, 2006), $c_1 = c_2 = 2$, $r_1 = r_2 = 0 \sim 1$ (Baltar and Fontane, 2006), w = 1 (Mendes et al., 2004), $w = 0.5 \sim 1.4$ (Elbeltagi et al., 2005). The parameters used in the current investigation are as follows: w = 1, w-damp = 0.9, c_1 = 1.5, c_2 = 2.0, r_1 = 2.05, r_2 = 2.05, n = 100, and I_{max} = 200. The GA model with crossover and mutation probabilities yields the best objective function value when w-damp = 0.9, n = 100. Each iteration of the algorithm results in a change in the value of the objective function. Similarly, after 200 iterations of the MPSO model. The algorithm takes longer to run and yields fewer desirable results with each subsequent iteration. This results in 200 total iterations of the MPSO algorithm. Figures 6 exhibit visual representations of these parameters for the multi-reservoir system.

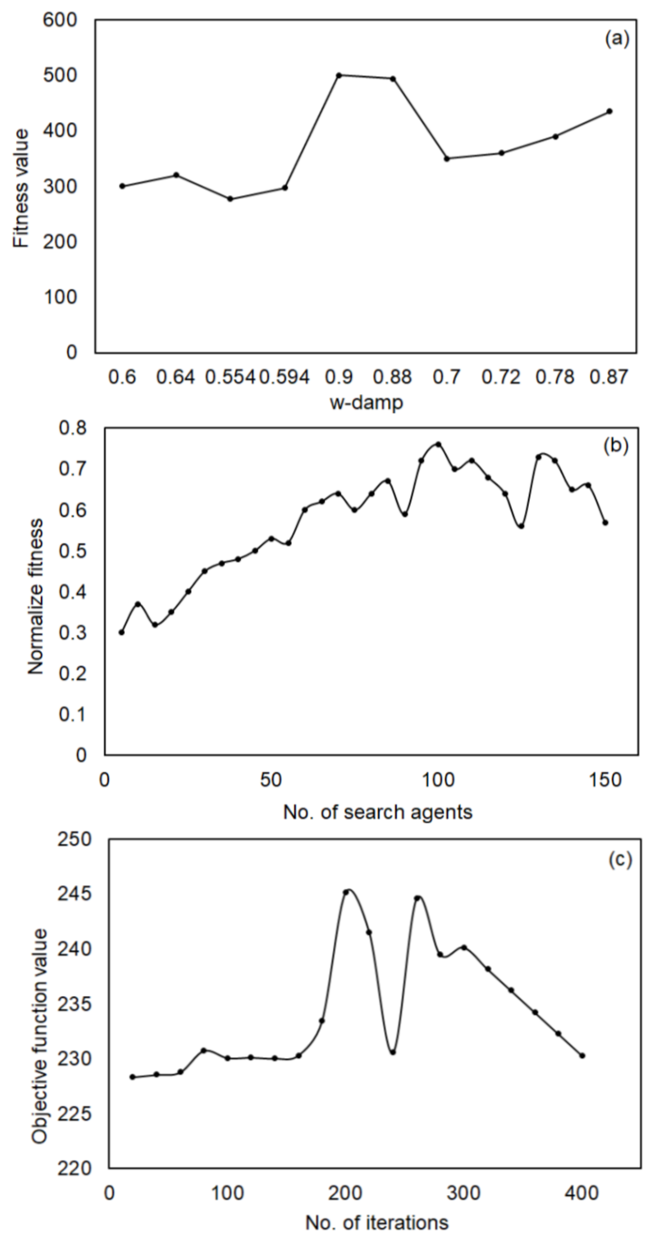

Figure 6. Sensitivity analysis by MPSO model (a) w-damp, (b) number of search agents, and (c) number of iterations.

Table 1. Criteria for Assessing the Accuracy of Models

Case Study	Algorithm	Evaluation Criteria					
Multi-reservoir System	Modified Particle Swarm Optimization	R^2	RMSE	MAPE	NMSE	MAE	MSE
		0.8794	1.3892	0.1003	0.1025	38.6689	1.9299

Table 2. Analysis of 10 Independent Runs

Number of Runs	MPSO	
	Optimal Value	CPU Time (s)
1	0.46	5.72
2	0.56	5.73
3	0.48	6.34
4	0.45	5.64
5	0.53	5.55
6	0.51	5.94
7	0.52	5.57
8	0.56	5.68
9	0.53	6.38
10	0.5	5.53
Best	0.45	
Worst	0.56	
Average	0.51	
SD	0.038006	
CV	0.001444	
Best CPU Time (s)	5.53	

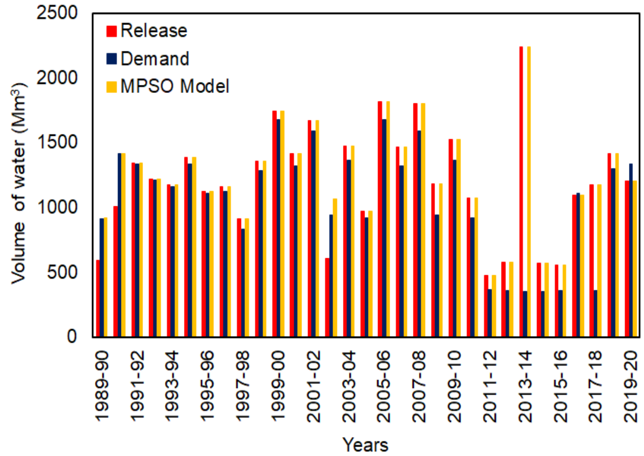

Figure 7. Modified particle swarm optimization's release policy is depicted graphically concerning the existing release and demand.

Table 3. Contrast the Standard Deviation and Coefficient of Variation Statistics Used in the Present Study to Those Used in the Work by Akbarifard et al. (2021)

Models	SD	CV
The Present Study (MPSO)	0.038006	0.001444
MSA	0.0029	0.0192
PSO	0.3078	0.8096
GA	0.5864	0.5458

Table 4. Comparison of Obtained Results Concerning Available Literature

Optimization Model		Performance Evaluation	
		R^2	RMSE
MPSO	Present Study	0.897	1.389
	Literature	0.834 (Akbarifard et al., 2021); 0.810 (ICA) (Sharifi et al., 2021)	2.82 (Akbarifard et al., 2021); 4.556 (Ehteram et al., 2018); 1.782 (HS) (Sharifi et al., 2021)

The operational policy for a study region from 1989 ~ 1990 to 2019 ~ 2020 was derived using the outcomes of a particle swarm optimization method. MATLAB was used to perform the method, and the resulting deficits during the period 1989 ~ 1990 to 2019 ~ 2020 are plotted graphically, with time t (years) on the X-axis and releases (M·m^3) on the Y-axis. When comparing the reservoir system operation model to the water release under existing policy, water shortages have only occurred in 1989 ~ 1990, 1990 ~ 1991, and 2002 ~ 2003 (refer to Figure 7).

The optimization model utilized historical data for 31 years, from June 1989 ~ 1990 to May 2019 ~ 2020. The effectiveness of a model is determined as per the methods described in Section 2.3 and enumerated in Table 1. In comparison to the existing operational policy, the MPSO model improves performance by an average of 100.31% in reliability, 85.02% in resilience, and 24.54% in sustainability, with a reduction in vulnerability of up to 69.54% (refer to Figure 8). To compare the efficiency of the MPSO model in multi-reservoir systems, we used the five statistical assessment criteria described in Section 2.3. Moreover, the model has the lowest error parameters (RMSE = 1.3892, MAPE = 0.1003, NMSE = 0.1025, MAE = 38.6689, and MSE = 1.9299), despite having the highest R^2 (0.8974) (refer to Table 1).

Table 2 shows that MPSO yielded the optimal ideal value of 0.45, the least-worst optimal value of 0.56, along with the average optimal value of 0.051, and the best standard deviation value of 0.038. Furthermore, MPSO displays the lowest coefficient of variation with a value of 0.001444 with the quickest CPU time with a length of 5.53 s. When it comes to obtaining maximum efficiency during reservoir management in the Ravishankar Sagar, MPSO is a reliable model because of its low SD. The fact that MPSO has the lowest CV is, nevertheless, worth noting. This suggests the fact that the MPSO has the least resiliency, or capacity to recover and resume normal operation after a break in operations. Despite having the lowest resiliency, MPSO was shown to be the most appropriate and reliable model for assessing and optimizing the Ravishankar Sagar reservoir in this study.

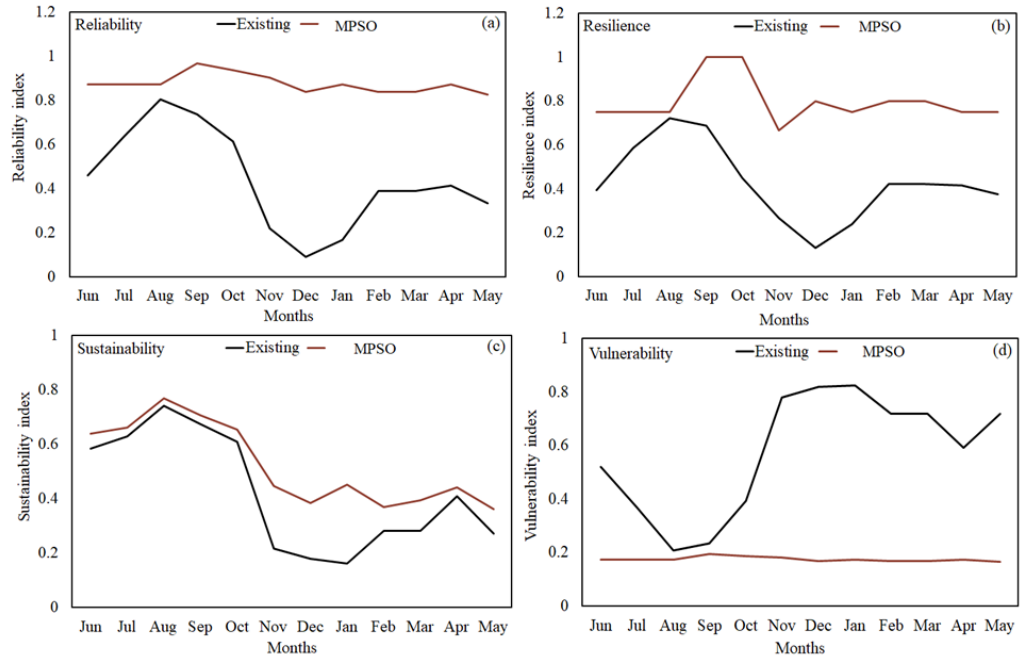

Figure 8. Graphical representation of release policy for swarm optimization concerning existing policy (a) reliability, (b) reilience, (c) sustainability, and (d) vulnerability.

Results from a comparable study performed by Akbarifard et al. (2021) on optimizing the Karun-4 hydropower reservoir using MSA, PSO, and GA are compared with the standard deviation and coefficient of variation methods used in the current study. The SD is found to be 0.038006 for the present study (MPSO), 0.0029 for MSA, 0.30789 for PSO, and 0.5864 for GA. Since the optimization values in the present study (MPSO) are most similar to the mean or predicted values, this suggests that the model is very reliable. However, the CV for the present study is 0.001444, and compared to MSA (0.0192), PSO (0.8096), and GA (0.5458), MSA is significantly better (refer to Table 3). Therefore, according to the results of the present case study conducted on the optimization of the Ravishankar Sagar reservoir, the MPSO proved to be the most robust and reliable model.

Comparing our findings to earlier research on multi-reservoir system operation optimization, we have come up with Table 4. As compared to other evolutionary algorithms available in the literature, GA has the best results in terms of coefficient of determination (R^2) and root mean square error, MPSO performs superior.

5. Conclusions

The present study concludes that MPSO is the optimal metaheuristic for optimizing the operation of dam reservoirs based on quantitative analysis as well as the existing operating policy (i.e., Standard Operating Policy [SOP]). In the present study, a multi-reservoir system's overall performance has improved by increasing average percentage changes to 100.31, 85.02, and 24.54% for reliability, resilience, and sustainability, respectively while vulnerability reduces up to 69.54%. In addition, the model had the maximum R^2 in the multi-reservoir system (0.8974), yet it had the least error parameters (such as RMSE = 1.3892, MAPE = 0.1003, NMSE = 0.1025, MAE = 38.6689, and MSE = 1.9299) in the system. Furthermore, MPSO is the more dependable metaheuristic algorithm mainly because it yields a higher SD than MSA, but MSA is the more robust metaheuristic due to its higher CV. This is based on comparisons with the best metaheuristic coming from an identical investigation on the Karun-4 hydropower reservoir according to Akbarifard et al. (2021). Additionally, the optimal value, worst optimal value, average optimal value, and standard deviation values for MPSO at Ravishankar Sagar reservoir are 0.45, 0.56, 0.51, and 0.038, respectively, making it the robust solution altogether. Throughout the test, MPSO consistently outperformed as compared to the PSO algorithm and other studied metaheuristics available in the literature in terms of optimizing the rates at which water was released and stored. Based on the results of this study, additional research could concentrate on hybridizing MPSO or implementing more sophisticated methodologies to enhance its performance in optimizing dam reservoir operations. However, this study is limited since it does not examine how climate change would affect the performance of Ravishankar Sagar Reservoir. Therefore, it is advised that the climatic situations at Ravishankar Sagar Reservoir operation be researched in addition to the hybridization of MPSO.

Furthermore, metaheuristic-based optimization algorithms may exhibit inefficiency when applied to large-scale problems due to their substantial demand for computational resources. Additionally, metaheuristic-based optimization algorithms are susceptible to premature convergence, which can cause them to become trapped in local optima instead of finding the global optimum. It's also possible that metaheuristic-based optimization algorithms have trouble finding an appropriate balance between exploration and exploitation, leading to less-than-ideal solutions. In conclusion, the fine-tuning of algorithm-specific parameters can prove to be a complex and time-consuming task. Moreover, applying these metaheuristic-based optimization algorithms to certain types of problems may lack straightforwardness and require careful consideration of their suitability and adaptability.

However, in the present study, the efficacy of the method relies heavily on parameter settings, posing challenges in identifying appropriate values for diverse problem instances. As the number of reservoirs and decision variables increases, the computational complexity of the Modified Particle Swarm Optimization increases substantially, making it less scalable and limiting its applicability to large-scale multi-reservoir systems. Finally, Modified Particle Swarm Optimization may struggle to handle constraints effectively, which results in implausible solutions that fall short of what is expected by the system.

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